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Bayesian Decoding of Neural Electrical Signals with a State-Space Model

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Abstract

Neural systems encode external stimulation information in the firing patterns of individual neurons. This paper deciphers how neural systems represent and transmit acupuncture information. First, the firings of the individual neuron are transformed into point process spike trains. Then a Bayesian approach to this problem based on state-space representations of point processes is described. We use this method to decode different types of manual acupuncture (MA), i.e. the stimulus oscillograms of the MAs are reconstructed from neural spike trains. These results are proved to be significant for neural data processing based on statistical analysis framework.

Keywords

Point Process; State-Space Model; Bayesian Decoding

Introduction

The relationship between neural spiking activity and a stimulus or behavior is the focus of neuro physiological investigation[1]. Describing the way a neuron represents information about a stimulus or behavior is the encoding problem. The dual problem of reproducing the stimulus or behavior from neural spike trains is the decoding problem. The ability to reconstruct a signal from observed neural activity provides a way of verifying that explicit information about the external world is represented in particular neural spike trains [2-3].

Since the spikes from a single neuron have stereotyped waveforms, neural representations of external stimulus signals are based on the frequency and timing of spike events. In addition, the neural spike trains generated in response to identical stimuli applied on separate occasions will not be identical and exhibit substantial variation even they may share common statistical features. These two fundamental facts suggest that neural spike train data might be effectively analyzed with the theory of point processes [4-6]. In this case, the temporal point processes are used to represent the times of the spiking events and to express the probability distribution of specific sequences of spike times.

In this article, we review the state-space approach for solving the neural decoding problem. A state-space estimation and inference framework is constructed by writing state models that describe the evolution of the stochastic signals to estimate, and intensity models for neurons that define the probability density of observing a particular sequence of spike times.

Here we establish the relationship between acupuncture stimulus oscillogram[7] and electrical signals of neuron through state-space model and reconstruct acupuncture signals of different types. This is a preliminary exploration that why MA with different types have different effects.

Experimental Materials and Methods

Description of Acupuncture Manipulation

The lifting-thrusting MA manipulation method contains three different types of manipulations based on the duration of lifting phase and thrusting phase, and they are lifting-thrusting reinforcing ('TB'), lifting-thrusting reducing ('TX') and uniform lifting-thrusting ('TC') manipulations respectively. When we carry out the MA manipulation, the depth of the acupuncture needle in the skin is real-timely recorded as an oscillogram [7], see Fig. 1.

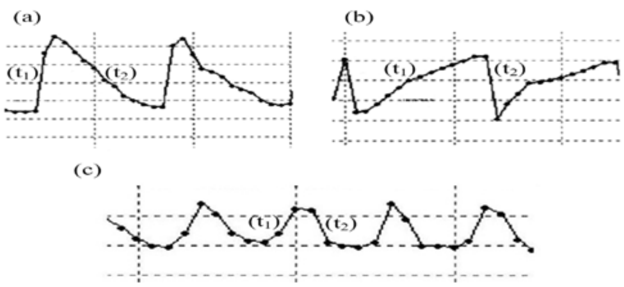

FIG. 1 SCHEMATIC DIAGRAM ABOUT THE OSCILLOGRAMS OF 'TB', 'TX' AND 'TC' MA

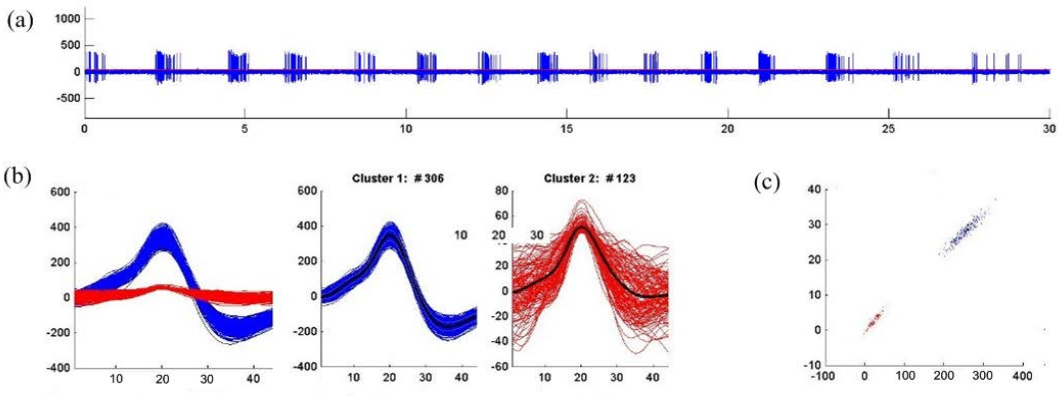

FIG. 2 SPIKE-SORTING OF SIGNALS

Acupuncture Neural Data Preprocessing

The neural spike activity evoked by acupuncture was recorded as continuous wide-band data, so spike detection and sorting should be accomplished firstly [7] to obtain spike train of individual neuron. After band-filtering the data between 300 and 3000 Hz, the spikes were detected by setting the threshold at

$$Thr = 3\sigma, \sigma = median\left\{\frac{|x|}{0.6745}\right\} \tag{1}$$

where x is signal after band-filtering and σ is the estimate of the standard deviation of the noise.The time series after band-filtering are shown in Fig. 2.

After the detection of spikes, the features of the spike shapes was extracted by the wavelet transform as inputs to the clustering algorithm. Each acupuncture stimulus evokes an obvious bursting, which contains the main information of acupuncture encoded by neuron. Then the most obvious class of spike train is transformed to point process.

Neural Spiking Model and Neural Decoding

Conditional Intensity Function

A point process is defined as a set of discrete events that occur in continuous time. For a neural spike train this would be the set of individual spike times[8]. Assume that the spiking activity of a single neuron is recorded for an observation interval $(0,T]$ during a neurophysiological experiment. Let $0 < u_1 < \cdots < u_j < \cdots < u_J \le T$ be the set of J spike times from the neuron, i.e. the point process observations. For $t \in (0,T]$, we define $N(t)$ as the number of spikes counted in the time interval $(0,t]$. Then the sample path of the spike times from the neuron is defined as the event $N_{0,t} = \{0 < u_1 < u_2,...,u_j \le t \cap N(t) = j\}$ with $j < J$ and it jumps 1 at the spike times and is constant otherwise. The sample path tracks the location and number of spikes in $(0,t]$ and therefore contains all the information of spike times[9].

A stochastic neural point process can be completely characterized by its conditional intensity function[8], which is

defined as

$$\lambda(t \mid H_t) = \lim_{\Delta \to 0} \frac{\Pr(N(t+\Delta) - N(t) = 1 \mid H_t)}{\Delta} \tag{2}$$

where H_t is the neuron's spiking history up to and includs time t and other relevant covariates. The conditional intensity function is a history-dependent rate function that generalizes the definition of the rate function of a Poisson process[8].

Using the conditional intensity function $\lambda(t \mid H_t)$, the joint probability distribution of a neural spike train $\{u_i\}_{i=1}^{n}$ in an interval $\left(0, T\right]$ is expressed as

$$p(\{t_i\}_{i=1}^{n}) = \left[\prod_{i=1}^{n} \lambda(u_i \mid H(u_i))\right] \exp\left(-\int_0^T \lambda(u \mid H(u))\right) \tag{3}$$

It is obviously that the first term on the right-hand side of (3) can be viewed as the probability density associated with observing action potentials at the actual spike times and the second term as the probability of not observing any other spikes anywhere in the interval.

Neural Point Process Model

Multiple factors simultaneously affect spiking activity of single neurons. The class of conditional intensity models that we use allows the analysis of the simultaneous effects of extrinsic covariates, internal spiking history, and concurrent neural ensemble activity. That is the conditional intensity processes with which we work can be written generally as

$$\lambda(t \mid H_t) = f(t, x_{[0,t]}, N_{[0,t)}, \{N_{[0,t)}^{c}\}_{c=1}^{C}) \tag{4}$$

where $x_{[0,t]}$ represents the values of a set of external covariates up to and including the present time, $N_{[0,t)}$ represents the neuron's spiking history, and $N_{[0,t)}^{c}\}_{c=1}^{C}$ represents the firing histories of other C neurons.

Here, we model a simple form of the conditional intensity function [9] in terms of the state process as

$$\lambda(k\Delta) = \exp(\mu + \beta x_k) \tag{5}$$

where μ is the log of the background firing rate and β is its gain parameter that governs how much the latent process modulates the firing rate of this neuron.

Assessing Model Goodness-of-fit

Before making an inference about a particular neural system from a statistical model, it is crucial to measure agreement between the model and the spike train data series, that is, to evaluate goodness-of-fit [9]. The time-rescaling theorem is a well-known result in probability theory to assess goodness-of-fit, and provides a direct means of measuring agreement between point process and a probability model intended to describe its stochastic structure [10]. The Kolmogorov–Smirnov test rejects the null-hypothetical model if any of the plotted points lie outside these bands.

Neural Decoding Analysis by State Estimation

Based on the discrete-time framework, the Bayesian decoding process can be constructed by using nonlinear recursive filter and fixed interval smoothing algorithm[9].

Decoding of Acupuncture Signals

State-Space Model of Acupuncture Electrical Signals

Now we illustrate the state-space framework for acupuncture electrical signals and solve the neural decoding problem. Neurons in spinal dorsal root ganglion fire preferentially when it response to the acupuncture stimulus.

The observation suggests that the acupuncture oscillogram can be reconstructed from neural spiking activity. We take the conditional intensity function of the neuron to be

$$\lambda(x_k) = \exp(\mu + \beta \cdot x_k) \tag{22}$$

where $\mu \in \mathbb{R}^1$ sets the baseline firing rate, and $\beta \in \mathbb{R}^1$ is the response strength of the neuron to acupuncture. Because the neurons are responsible for the generation and conduction of the electrical signal evoked by acupuncture in the initial stages, we set up this model under the assumption that the neuron has firing properties that do not depend on its own spike history or that of any other neuron. Therefore this activity comprises an inhomogeneous Poisson process. The observation interval is partitioned into uniform bins with size of Δ. The state evolution equation is taken to be

$$x_k = \rho x_{k-1} + \varepsilon_k \tag{23}$$

where ρ is a correlation coefficient, ε_k is a Gaussian random variable with mean zero and variance σ_ε^2.

Reconstructing Acupuncture Oscillogram

We applied the Bayesian decoding algorithm to data recorded from the spinal dorsal root ganglion of experiment rats, on which different types of MA ('TB','TX' and 'TC') are taken. The true acupuncture oscillograms of different types ('TB','TX' and 'TC' MA) are also simulated based on the acupuncture stimulus times. The whole time interval for each record is $T = 20$ seconds. The resolution of the spike trains is 1 msec, and the state equations are updated at 1 msec.

Similar to the analysis of signals generated by simulation, acupuncture oscillograms are also reconstructed from the neural spike trains by Bayesian decoding algorithm. First, we estimate the parameters in equations by maximum likelihood estimation. The parameter estimates from the EM algorithm are shown in Table 1.

TABLE 1 THE PARAMETER ESTIMATES FOR ACUPUNCTURE SIGNALS.

MA \ Parameter	μ	β	ρ	σ_ε^2
TB	-4.350	0.695	0.992	0.022
TX	-4.316	0.446	0.991	0.025
TC	-3.507	0.272	0.990	0.030

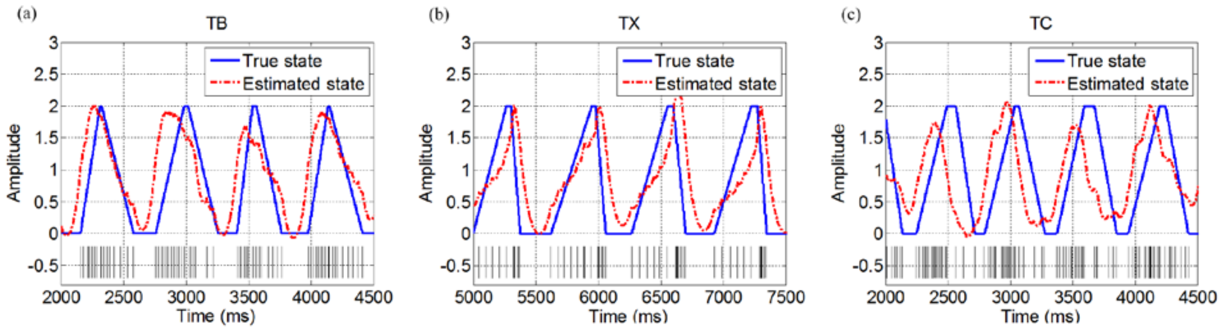

FIG. 3 THE ESTIMATED OSCILLOGRAMS

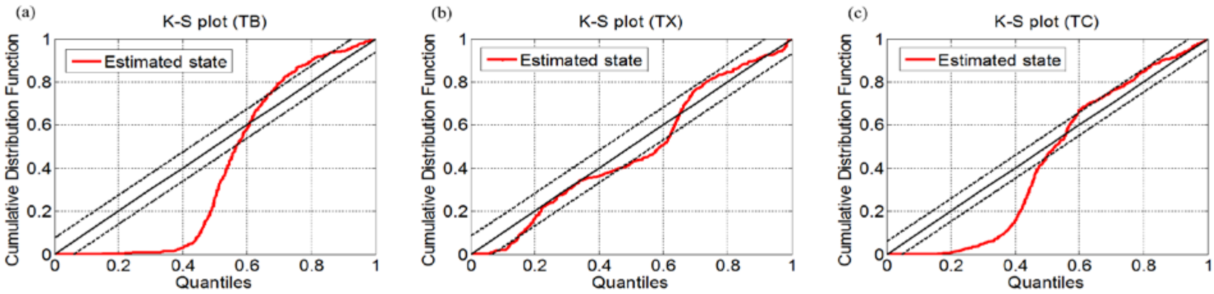

FIG. 4 THE K-S PLOTS OF THE MODEL ESTIMATE

After the parameters were estimated, acupuncture oscillograms were reconstructed from neural spike trains. Fig. 6 shows a fragment of the estimated states of three different types of MA respectively. For the 'TB' MA manipulations, the oscillogram has the bigger duration of ascending branch (t1) and smaller duration of descending branch (t2), as seen from Fig. 6(a); for the 'TX' MA manipulations, the oscillogram has the smaller duration of ascending branch (t1) and bigger duration of descending branch (t2), as seen from Fig. 6(b); the durations of ascending branch (t1) and descending branch (t2) are approximately the same in the oscillogram of 'TC' MA manipulation, as seen from Fig. 6(c). Overall, decoded acupuncture oscillograms captured mostly fluctuations as the simulated state shown and showed the basic characteristics of each MA manipulations. The K-S plots are shown in Fig. 7 to assess model goodness-of-fit. For 'TB' MA, the models lie within the 95% confidence limits, indicating close agreement between the overall model fit and the data. For both 'TX' and 'TC' MA, the fit of model lies within the confidence limits except at the small quantiles.

Conclusions

We have introduced Bayesian decoding algorithm to the studies of acupuncture neural electrical signals, i.e. we construct the relationship between different types of MA and the corresponding neural spike trains. The neural spike trains can be described by point process modeling based on the conditional intensity function. To reconstruct acupuncture oscillogram from point process spike trains we have used state-space models which are well suited for describing these changes in neural firing properties. The present study shows that the encoding of different acupuncture manipulations have their own features. Different MA oscillogram can be reconstructed from the neural spike trains by decoding algorithm even in a single trial. These results imply that different encoding features are related to different effects which different acupuncture manipulations have.

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